Implications of Western Pacific Tropical Cyclones' RSD's to the Bulk Microphysics Schemes and Quantitative Precipitation Estimation Using Machine Learning Models

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Introduction

- The microphysics parameterization schemes used in NWP models are
- Bulk microphysics schemes
  - One moment
  - Two moment
  - Three moment

- Spectral bin microphysics schemes
- Lagrangian particle based schemes

- For operational purposes one moment bulk microphysics schemes are used because of efficiency and low computational cost.

Introduction

- These schemes assume the particle size distribution as some statistical distribution like exponential or gamma
- In one moment schemes two gamma parameters μ and No are assumed as constants and the other parameter Λ can be diagnosed from the prognostic variable mass mixing ratio Q.
- But the assumption is not true!

Introduction

- How to improve one moment bulk microphysics schemes:
  - Prescribe No from the look-up table
  - Calculate the second parameter Λ from a relationship (Λ-No) obtained from the observed RSD
  - The third parameter μ from the mass mixing ratio and the other two gamma parameters (Q, Λ, No --> μ)

Data & methods

Data sets used (2005-2019)

- JTWC tropical cyclones track information
- JWD data from north Taiwan (NCU)

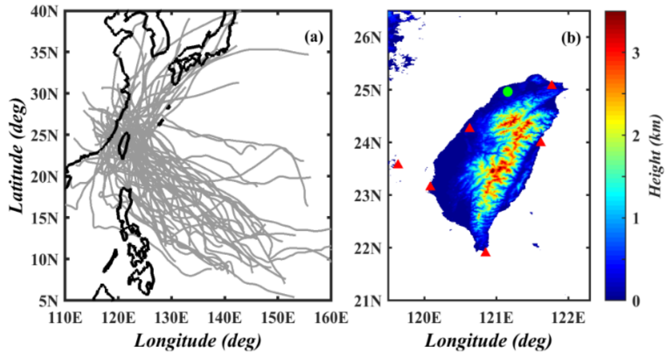


Fig. (a) WP TCs' tracks **(b)** location of JWD (green filled circle) in north Taiwan.

TC rainfall @ disdrometer site:

Distance between TC center and JWD site ≤ 500 km

The rain drop concentration N(D) (m^{-3} mm^{-1}) from the JWD is given as:

$$N(D)(m^{-3}mm^{-1}) = \sum_{i=1}^{20} \frac{n_i}{A \times \Delta t \times V(D_i) \times \Delta D_i}$$

where , n_i is the number of drops reckoned in the size bin i, A (m^2) and Δt are the sampling area and time, D_i (mm) is the drop diameter for the size bin i , ΔD_i is the corresponding diameter interval (mm), V_j (m/s) is terminal velocity of drops of diameter D_i

R (rainfall rate, mm h^{-1}), *Z* (radar reflectivity, dB*Z*), N_t (total number concentration, m^{-3}), and *LWC* (liquid water content, gm^{-3}) are estimated:

$$R\ (\text{mm h}^{-1}) = 6\pi \times 10^{-4} \sum_{i=1}^{20} V(D)N(D)\, D^3\, \Delta D$$

$$Z\ (\text{dBZ}) = 10 \times log_{10}\left(\sum_{i=1}^{20} N(D)D^6 \Delta D\right)$$

$$N_t\ (\text{m}^{-3}) = \sum_{i=1}^{20} N(D)\, \Delta D$$

$$LWC\ (\text{g m}^{-3}) = \frac{\pi}{6}\, \rho_w \sum_{i=1}^{20} N(D)\, D^3 \Delta D$$

$$D_m\ (\text{mm}) = \text{M4/M3} \qquad M_n = \int_{D_{min}}^{D_{max}} D^n\, N(D) dD$$

Data & methods

Gamma distribution and moments method:

The Gamma distribution function: $N(D) = N_o D^{\mu} \exp(-\Lambda D)$

The nth moment of the gamma distribution: $M_n = \int_0^{\infty} D^n n(D) dD = N_o \Lambda^{-(\mu+n+1)} \Gamma(\mu + n + 1)$

$M_2M_3M_4$, $M_2M_4M_6$, $M_3M_4M_6$, consecutive moments $M_nM_{n+1}M_{n+2}$

The gamma distribution parameters in terms of 2nd, 3rd, and 4th moments (**M_2, M_3, and M_4**) are expressed as (Smith and Kliche, 2005):

$$\mu = \frac{Q(m+1) - (m+2)}{1 - Q} \qquad \lambda = \frac{M_2\,(m + \mu + 1)}{M_3} \qquad N_0 = \frac{M_m \Lambda^{(m+\mu+1)}}{\Gamma(m + \mu + 1)}$$

Here, $Q = \frac{M_2 M_4}{{M_3}^2}$. With m=2, the above shape, slope and intercept parameters corresponds to 2nd, 3rd and 4th moments

The gamma distribution parameters in terms of 2nd, 4th, and 6th moments (**M_2, M_4, M_6**) are expressed as (Ulbrich and Atlas, 1998):

$$\mu = \frac{(7 - 11\eta) - \sqrt{\eta^2 - 14\eta + 1}}{2(\eta - 1)} \qquad \lambda = \sqrt{\frac{M_2 \Gamma(\mu + 5)}{M_4\,\Gamma(\mu + 3)}} \qquad N_0 = \frac{M_4 \Lambda^{(\mu+5)}}{\Gamma(\mu + 5)} \qquad Here, \eta = \frac{{M_4}^2}{M_2 M_6}$$

Data & methods

Gamma distribution and moments method:

The gamma distribution parameters in terms of 3rd, 4th, and 6th moments (**M_3, M_4, M_6**) are expressed as (Ulbrich, 1983):

$$\mu = \frac{(11G - 8) + \sqrt{G(G + 8)}}{2(1 - G)} \qquad \lambda = \frac{M_3(\mu + 4)}{M_4} \qquad N_0 = \frac{M_3 \Lambda^{(\mu+4)}}{\Gamma(\mu + 4)} \qquad Here, G = \frac{{M_4}^3}{{M_3}^2 M_6}$$

The gamma distribution parameters can be expressed by any three consecutive moments (i.e., ***M_n*, *M_{n+1}*, *M_{n+2}***) can be expressed as (Smith, 2003; Smith et al., 2009)

$$\mu = \frac{B(n + 1) - (n + 2)}{(1 - D)} \qquad \Lambda = \frac{M_n(n + \mu + 1)}{M_{n+1}} \qquad N_0 = \frac{M_n \Lambda^{(n+\mu+1)}}{\Gamma(n + \mu + 1)} \qquad \text{Where, B} = \frac{M_n M_{n+2}}{{M_{n+1}}^2}$$

Results & Discussion

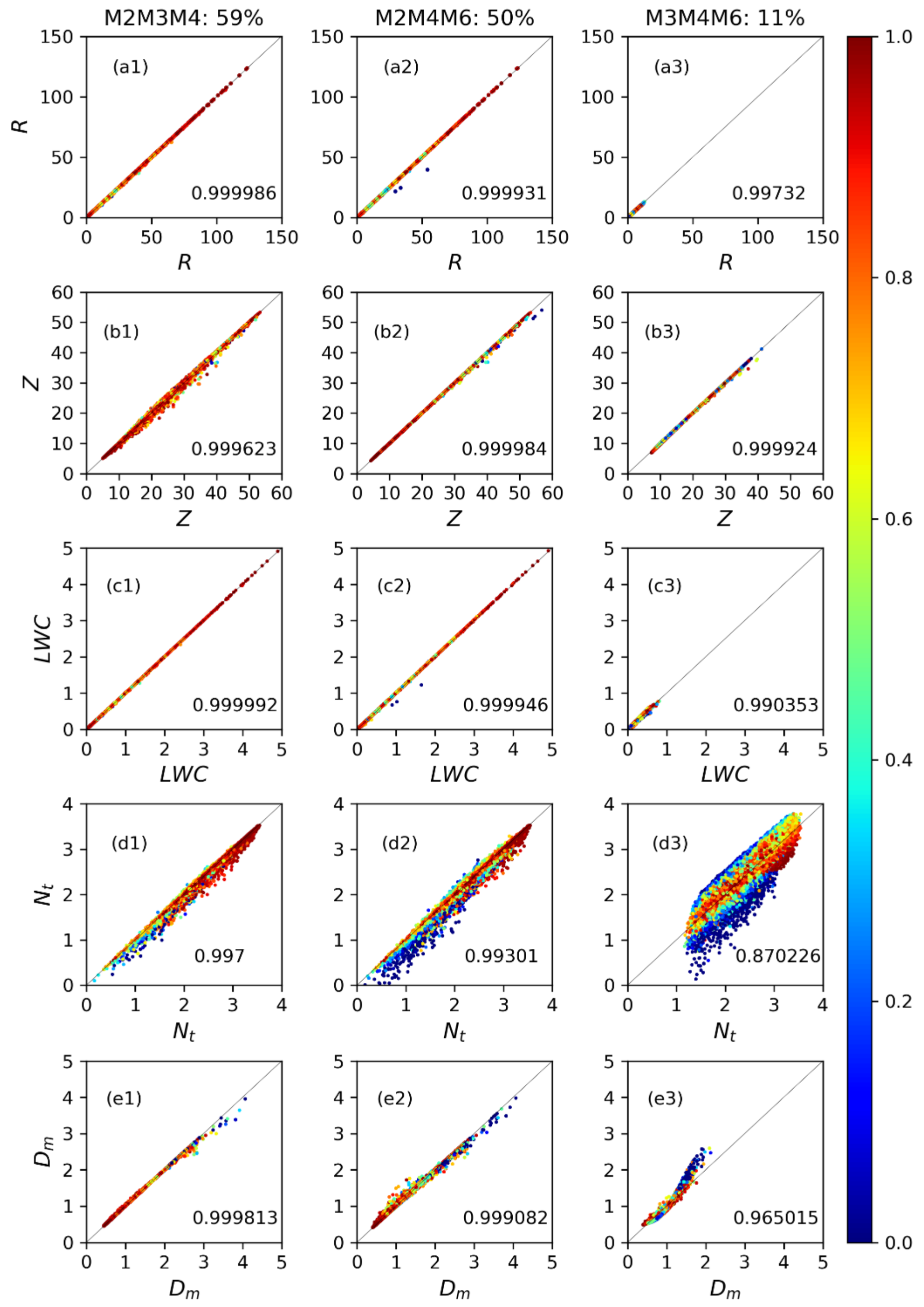


Figure. Comparison of RSD parameters (R in mm h^{-1}: first row, Z in dBZ: second row, LWC in g m^{-3}: third row, N_t in m^{-3}: fourth row, and D_m in mm: fifth row) estimated from the observation (X-axis) and gamma distribution (GD) fits (Y-axis) using second, third, and fourth moments ($M_2M_3M_4$: first column), second, fourth, and sixth moments (M_2M4M_6: second column), third, fourth, and sixth moments ($M_3M_4M_6$: third column).

Results & Discussion

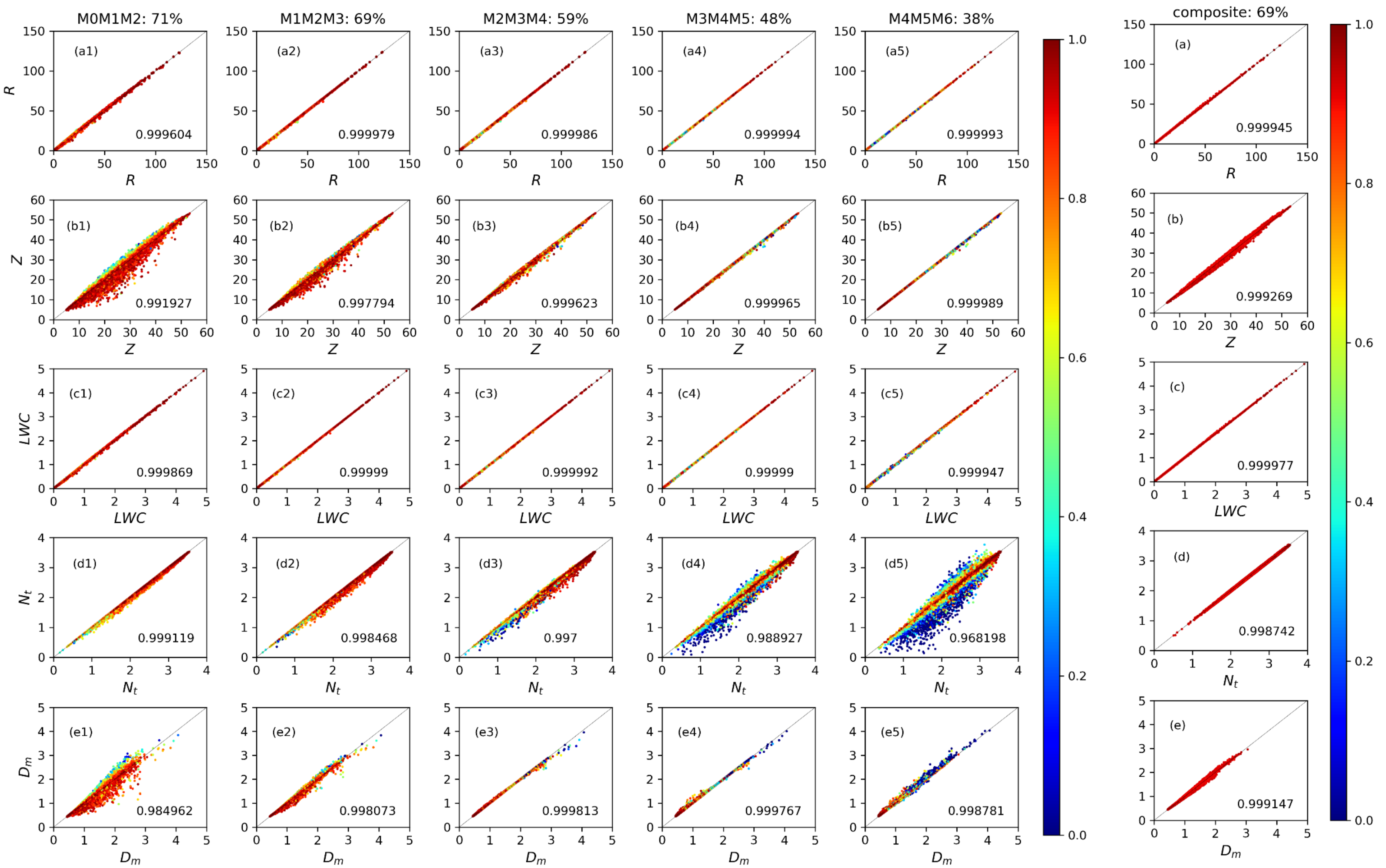


Figure. Comparison of RSD parameters (R in mm h^{-1}: first row, Z in dBZ: second row, LWC in g m^{-3}: third row, N_t in m^{-3}: fourth row, and D_m in mm: fifth row) estimated from the observation (X-axis) and gamma distribution (GD) fits (Y-axis) using three consecutive moments (M_{012}: first column, M_{123}: second column, M_{234}: third column, M_{345}: fourth column, M_{456}: fifth column) and hybrid moments (sixth column).

Relationships among gamma parameters (μ , λ and N_o)

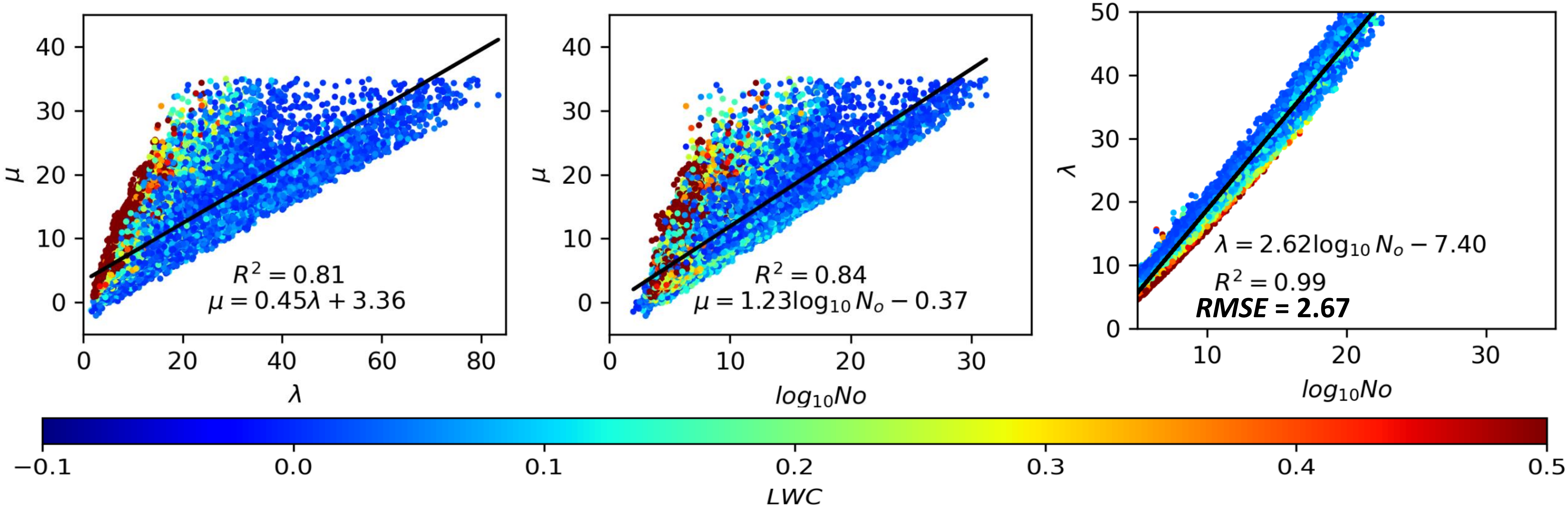


Figure. Scatter plots of shape–slope parameter (μ– λ), shape–intercept parameter (μ–$\log_{10}N_0$), and slope–intercept parameter (λ–$\log_{10}N_0$), and with liquid water content (*LWC*).

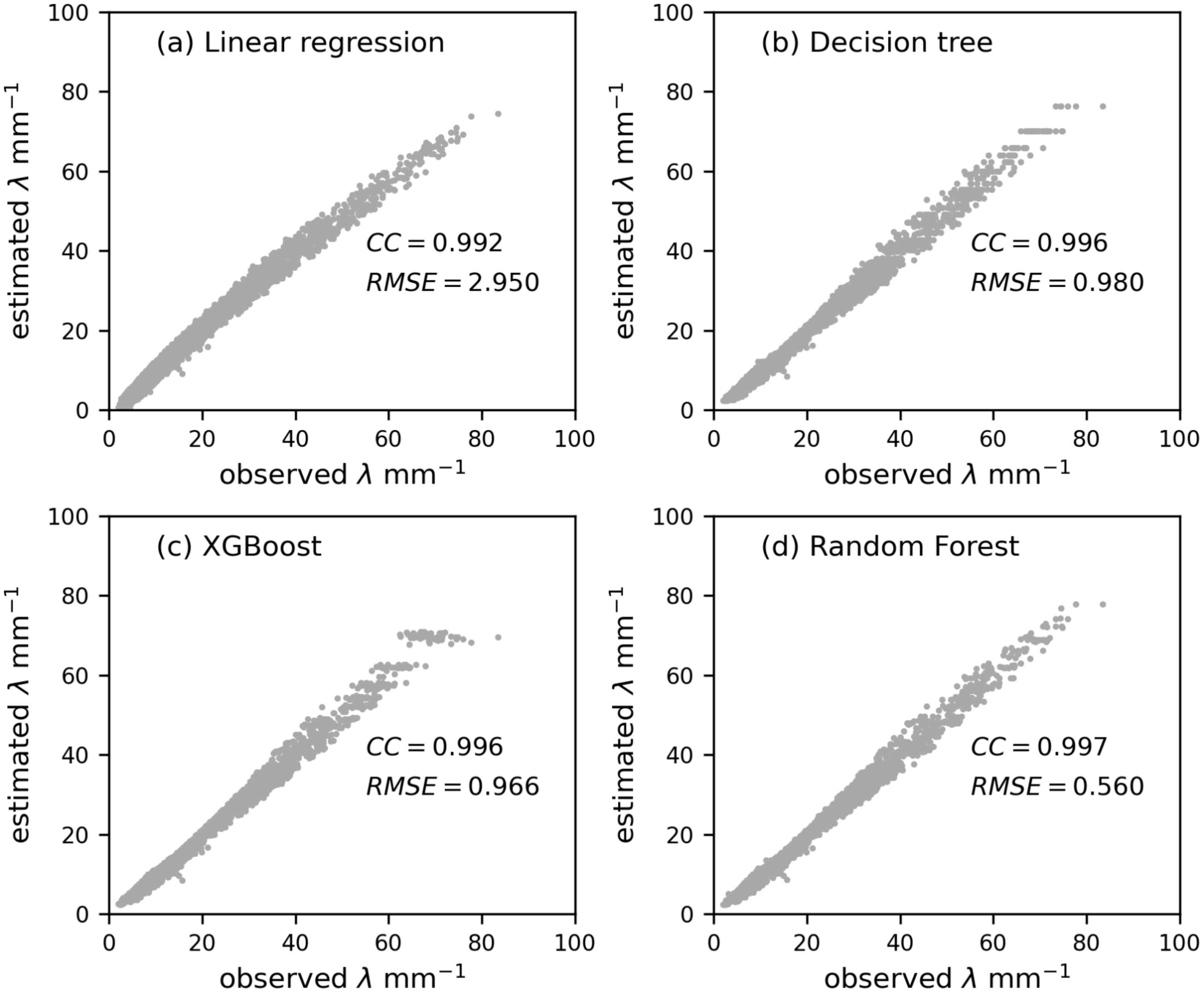
Results & Discussion

Machine learning models:

1. Decision Tree
2. XGBoost
3. Random Forest

Training data – 70%
Test data – 30%

Results & Discussion



Radar reflectivity and rainfall rate ($Z-R$) relations

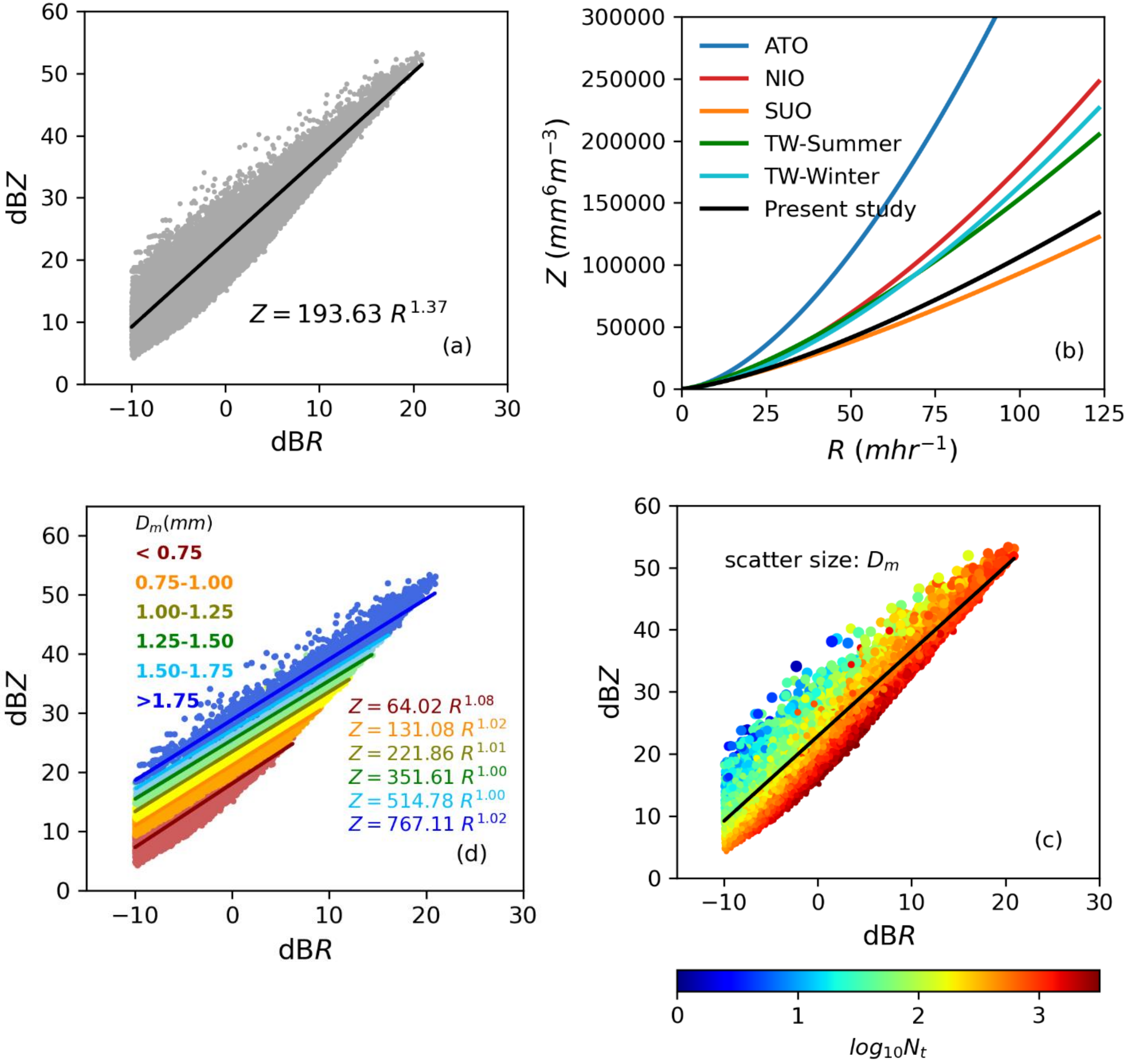
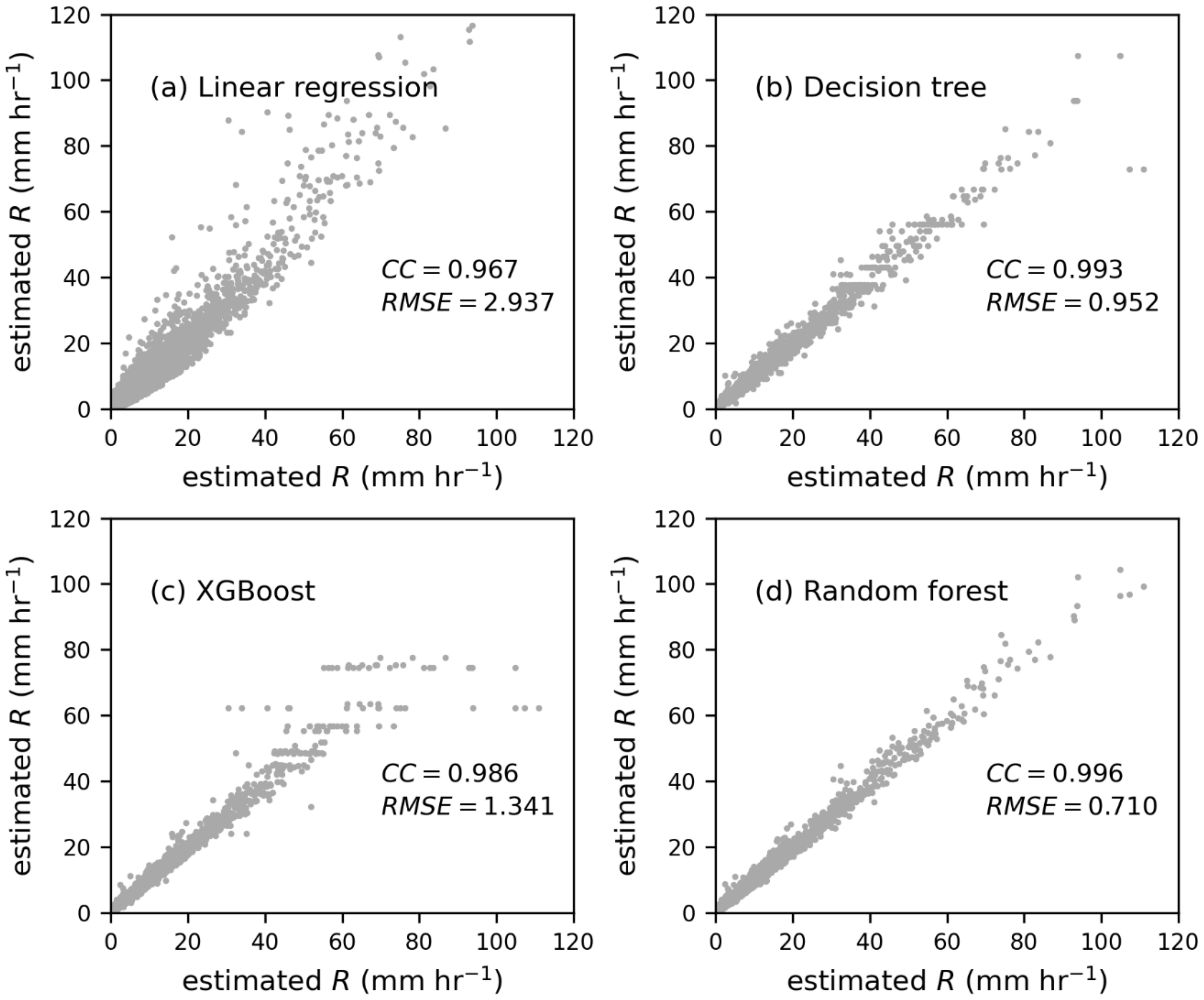


Figure. Radar reflectivity and rainfall rate relations.

Oceanic region	Z-R relations	Reference
Atlantic Ocean (ATO)	$Z = 186.00\ R^{1.63}$	Hopper et al., (2020)
North Indian ocean (NIO)	$Z = 142.04\ R^{1.55}$	Radhakrishna and Narayana Rao, (2010)
Southern Ocean (SUO)	$Z = 234.00\ R^{1.3}$	Deo and Walsh, (2016)
Taiwan-Summer	$Z = 266.42\ R^{1.38}$	Seela et al., (2018)
Taiwan-Winter	$Z = 129.76\ R^{1.55}$	Seela et al., (2018)

Results & Discussion



Conclusions

- The radar reflectivity and rainfall rate relations of Western Pacific tropical cyclones (WP TCs) are distinctly different from that of the other oceanic TCs.

- The rain fall rates estimated with Machine learning approaches (inputs: Z & D_m) showed superior performance over the linear regression Z-R relation.

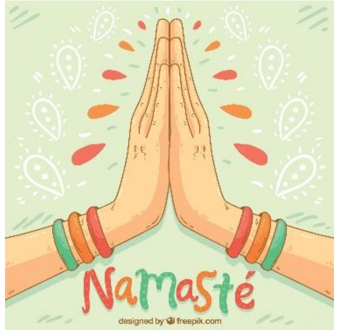
- The RSD parameters estimated with hybrid/composite moments over the fixed three moments method are well agreed with observation.

- Among slope-shape, shape-slope, and slope-intercept parameter relations, the he three kind relationships among slope, shape and intercept parameters parameters are close to one-to-one line for Slope–intercept parameter ($\lambda-\log_{10}N_0$),

- Among shape–slope parameter ($\mu-\lambda$), slope–intercept parameter ($\lambda-\log_{10}N_0$), shape–intercept parameter ($\mu-\log_{10}N_0$) relations, the less spread in data points from one-to-one line is observed for $\lambda-\log_{10}N_{0.}$

- The slope parameters estimated using machine learning approaches (inputs: $\log_{10}N_0$ and LWC) demonstrated better results over the linear $\lambda-\log_{10}N_0$ relations.

- Present study demonstrates that, better estimates of rainfall rates and slope parameter can be achieved through random forest approach over linear regression methods.



Thank you for listening !!

n^{th} Moment (M_n): $$M_n = \int_{D_{min}}^{D_{max}} D^n \, N(D) dD$$

Moment	Microphysics Variable
0	Particle/drop concentration(m^{-3}): $N = M_0 = \int_0^\infty n(D)dD$
3	Mass mixing ratio ($kg \cdot kg^{-1}$): $Q = M_3 = \frac{\pi \rho w}{\rho} \int_0^\infty D^3 n(D)dD$
6	Radar Reflectivity ($mm^6\, m^{-3}$): $Z = M_6 = \int_0^\infty D^6 n(D)dD$

Microphysics parameterization schemes

- Bulk microphysics schemes: assume PSD/RSD/DSD to be certain functions
  - One moment (1)
  - Two moment (2)
  - Three moment (3)

- Spectral bin microphysics schemes:
  calculate PSDs/DSDs/RSDs by solving explicit microphysical equations

- Lagrangian particle-based schemes

One moment Microphysics Parameterization Schemes:

$$\frac{\partial Q_R}{\partial t} = \underbrace{-V \cdot \nabla Q_R}_{\text{Advection term}} + \underbrace{\nabla \cdot K_m \nabla Q_R}_{\text{Diffusion term}} + \underbrace{P_R}_{\text{Production term}} + \underbrace{\frac{1}{\rho}\frac{\partial (\rho U_R Q_R)}{\partial z}}_{\text{Fallout term}}$$

$$P_R = P_{RAUT} + P_{RACW} + \ldots$$

$$P_{RACW} = \frac{\pi E_{RW} n_{0R} a Q_{CW} \Gamma(3+b)}{4\lambda_R^{3+b}} \left(\frac{\rho_0}{\rho}\right)^{1/2}$$

$$U_R = \frac{a\Gamma(4+b)}{6\lambda_R^{b}} \left(\frac{\rho_0}{\rho}\right)^{1/2}$$

$$n_R(D) = n_{0R}\, e^{-\lambda_R D}$$

n_{0R}(intercept) $= 8 \times 10^{-2}\ cm^{-4}$

λ_R (slope) $= \left(\frac{\pi \rho_W n_{0R}}{\rho Q_R}\right)^{0.25}$

Lin et al. 1983;

GFDL microphysics scheme in HALFS

$Q_R \uparrow$ → $\lambda_R \downarrow$ → Larger increase in larger drops number concentration

↓

Reflectivity ↑

Improve bulk microphysics parameterization schemes

- One-moment bulk microphysics parameterization Schemes
  - Prescribe one parameter through a look-up table;
  - Calculate the second parameter from a relationship identified from the observations;
  - Diagnose the third parameter from the mixing ratio;

- Two-moment bulk microphysics parameterization Schemes
  - A gamma distribution can be fully determined from a relationship identified from the observations and two prognostic variables (mixing ratio and number concentration)